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Methodological uncertainties in estimating carbon storage in temperate forests and grasslands

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ABSTRACT

Carbon sequestration is an essential ecosystem service (ES) for climate change mitigation. For reasons of simplicity this ES is often quantified considering carbon storage in four carbon pools: aboveground biomass, belowground biomass, dead organic matter and soil organic carbon. Indicators of these four pools are estimated by modelling, reference values, or field methods and data processing of different complexity levels which requires comparing estimations. In order to facilitate the assessment of carbon pools, e.g. in environmental impact assessment, a fast, reliable and easily applicable method is required. First, using a systematic literature review we identified frequently used field methods for estimating carbon pools for forests and grasslands, two ecosystems playing a key role in global climate regulation. Second, from this review we developed field methods for indicators of each carbon pool – aboveground biomass, belowground biomass, soil organic carbon and dead organic matter – in both ecosystem types. We applied these methods in a set of forest and grassland plots in the Grenoble region (France) and asked i) how comparable and consistent are alternative methods for each carbon pool? ii) what is the variability of estimates between these methods? and iii) which level of simplicity has an acceptable level of uncertainty? Thereby, we conducted for the first time method comparisons for all four carbon pools. We based our method comparisons on the quality of the linear relationships between methods and their level of accuracy relatively to the chosen reference methods (the method assumed to be the closest to the actual carbon stock). For most carbon pools – e.g. aboveground biomass and soil organic carbon, both major carbon stocks – selected alternative methods were comparable and consistent with the reference method. Third, we built on these results to suggest easy and quick field methods for each carbon pool in each ecosystem type with accuracy levels between 10 and 20%. We provide guidelines together with associated uncertainty levels to scientists and practitioners aiming to estimate the ecosystem service of global climate regulation from carbon stocks in terrestrial ecosystems. The guidelines also allow adjusting method selection to human, knowledge and financial resources available in the study context.

1. Introduction

In the face of accelerating climate change (Smith et al., 2015) and of its observed and projected impacts on ecosystems and biodiversity (Scheffers et al., 2016), global climate regulation by ecosystems is an essential ecosystem service to society (Díaz et al., 2018). Quantifying terrestrial, aquatic and marine ecosystems ability to reduce atmospheric greenhouse gases concentrations is therefore essential, especially if international political and economic mechanisms for regulating carbon emissions and sequestration are to be operational (Díaz et al., 2018). Carbon sequestration in ecosystems supports the essential ecosystem service (ES) of climate regulation which benefits to human well-being at global scale (MEA, 2005) and is one of Nature's eighteen essential Contributions to People (Díaz et al., 2018). The global climate regulation service is a regulating ecosystem service mitigating climate change induced by anthropogenic emissions, and is mainly supported by plant photosynthesis and the activity of soil microorganisms (Dignac et al., 2017). Given international accounting and trading mechanisms, this ES is often estimated by monetary valuation (Luisetti et al., 2013; Tardieu et al., 2013). Economic (or instrumental), and specifically monetary valuation, is one of the values that can be attributed to an ES, but is only one of the three pillars of integrated valuation which also includes biophysical (or intrinsic) and social (or relational) values (Jacobs et al., 2018; Pascual et al., 2017).

To quantify the biophysical value of global climate regulation carbon sequestration is commonly quantified by measuring or

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estimating carbon fluxes between the atmosphere and ecosystems. Its direct measurement requires significant equipment (flux towers (Gilmanov et al., 2006); eddy covariance systems (Sándor et al., 2016)), resources, and knowledge. Alternatively, it is often estimated through the measurement or modeling of ecosystem carbon fixation, or calculated as the difference of carbon stocks, the carbon actually stored in ecosystems, between two dates. Carbon storage is thus a proxy often used to simplify the estimation of the ecosystem service of global climate regulation. Carbon storage is the amount of carbon present in one or more carbon pools of an ecosystem at a specific time. However, care should be taken as carbon stock estimation is a rough proxy for climate regulation which does not reflect the variations of carbon flux speed, another consequence of climate change (Ziegler et al., 2017). For a more comprehensive estimation of the ES of global climate regulation, carbon stock estimation should be combined with flux measurements.

The estimation of terrestrial carbon storage usually considers four carbon pools. First aboveground biomass (AGB) includes aboveground parts of trees (stem, branches, and leaves), shrubs and herbaceous plants. The belowground biomass pool (BGB) covers coarse and thin tree roots but also shrub and herbaceous roots. The dead organic matter pool (DOM) includes dead organic matter on the soil surface as well as litter and dead wood. Lastly the soil organic carbon pool (SOC) is considered across soil layers. These carbon pools are used for field estimation of carbon storage using dedicated indicators in tools for practitioners such as the Toolkit for Ecosystem Service Site-based Assessment (TESSA) (Peh et al., 2013). They are also often used for modeling the global climate regulation service, for instance in the free and open source ES model InVEST (www.naturalcapitalproject.org), which has been applied to Mediterranean forest (Bottalico et al., 2016), tropical forest in Brazil (Chaplin-Kramer et al., 2015), and across different land cover types of the Spanish Basque Country (Palacios-Agundez et al., 2015).

Different methods are available for estimating each of the four carbon pools. These include modeling, field measurements coupled with potential laboratory and mathematical analyses, and use of values from literature reviews. For instance for AGB, carbon storage can be estimated using forest growth models (e.g. CenW, (Dymond et al., 2012)), tree measurements in the field coupled with allometric equations (Conti and Díaz, 2013), or through data analysis from national forest inventories or forest studies (Cademus et al., 2014; Poorter et al., 2016). For SOC, carbon storage can be estimated using a soil carbon model (Bandaranayake et al., 2003), the IPCC (Intergovernemental Panel on Climate Change) standard value (Zandersen et al., 2016) or using direct field measurements (Preger et al., 2010).

At local scales there is increasing demand for the inclusion of ecosystem services in environmental impact assessment and land planning (Albert et al., 2016; Diehl et al., 2016). This requires the development of easily applicable, consensus methods that enable comparability between studies and some consistency across carbon storage estimates. In addition, there is a need to assess uncertainties associated with common methods for quantifying the four carbon pools, so that different methods of varying complexity applied in different studies may be compared.

In this study, we assessed methodological uncertainties associated with methods for field measurement of indicators of each carbon pool. Rather than identifying the ”best” universal method, we aimed to provide an assessment of existing methods to help guide researchers and practitioners in method selection and highlight their associated risks. Specifically, we asked: i) how comparable and consistent are the different methods for each carbon pool?, ii) what is the variability of estimates between these methods?, iii) which level of simplicity has an acceptable level of uncertainty?

To answer these questions we first identified existing methods for each carbon pool based on a systematic literature review. Second we assessed field protocols for both tree-dominated and grass-dominated ecosystems. Forest ecosystems store significant carbon in their AGB pool under temperate, tropical and boreal climatic conditions (Bonan, 2008). The importance of grassland ecosystems for carbon storage, especially in their soil pools has also been repeatedly emphasized (Lal, 2004; Minasny et al., 2017). Protocols were tested in the Grenoble region (France), which comprises a broad range of temperate forest and grassland ecosystems. Third, we compared the carbon stock estimations measured with the different field methods to the selected reference method, providing a first comprehensive comparison of field methods for the four major carbon pools. Based on the analysis of these results we discuss for each carbon pool the relative merits of the methods in balancing simplicity and/or rapidity, and the reduction of uncertainty. We expected estimation methods of major and well-studied carbon pools – i.e. forest AGB and SOC – to be more numerous and more easily simplified thanks to greater knowledge of their characteristics and functioning and to abundant data. Conversely, for overlooked carbon pools such as BGB and dead organic matter, we supposed that fewer methods would be available and that they would be less accurate due to both fundamental knowledge and data gaps.

2. Methods

2.1. Literature review

We reviewed the literature to determine the current range of indicators and methods used to estimate carbon storage. *ISI Web of Knowledge* was searched in a three stage process using sets of key-words for which all results were systematically checked between 20/03/2016 and 13/04/2016. The first step focused on carbon sequestration/storage modeling to identify variables considered for this service. The second step focused on literature specific to ecosystem services and the underlying ecological functions/processes to find field methods for estimating carbon sequestration/storage. The third step broadened the search to ecological literature not referring explicitly to the ecosystem service concept and dealing with carbon storage estimation in the field. Ultimately, focusing on modeling was sufficient, as these sets of key-words produced 360 papers addressing carbon storage modeling, biophysical measures and their combination, with biophysical measures being used for the model calibration (Table A1 in Appendix A).

A first selection of paper titles and abstracts yielded 243 papers. Papers were discarded if carbon sequestration or storage was not estimated explicitly or was considered only from an economic perspective. A second selection was done after reading the methods section. Papers which did not detail the model or method used were discarded, leaving 157 papers for detailed analysis (Appendix B). A synthetic table was filled with information from the selected papers (Table A2 in Appendix A). The Methods sections of the selected papers were reviewed. The more common indicators and field methods for each carbon pool were retained and considered in depth in order to be tested in the field as presented below.

2.2. Study area

The urban area of Grenoble (45°11′ N/5°43′ E) is a basin surrounded by three mountain ranges: Belledonne, Chartreuse, and Vercors. It also comprises plateaus and valleys, and is shaped by the confluence of three rivers: the Isère, the Drac and the Romanche, supporting fertile floodplains with arable lands and numerous wetlands (Vannier et al., 2016). Overall, this richness of physical and natural features shapes a high diversity and heterogeneity of landscapes which allowed us to work on a wide range of ecosystems, representative of variation in similar temperate regions. This study focused on an array of typical forest (10 sites: 4 on valley moraine soil, 3 on alluvial soil and 3 forests on slopes) and grasslands (11 grassland plots: 8 humid grasslands for AGB of which 3 were considered for SOC -, and 3 mesophilic grasslands) (Table C1 in Appendix C). All sites were located within the regional ecological corridors network, or within the regional “Sensitive Natural Areas”

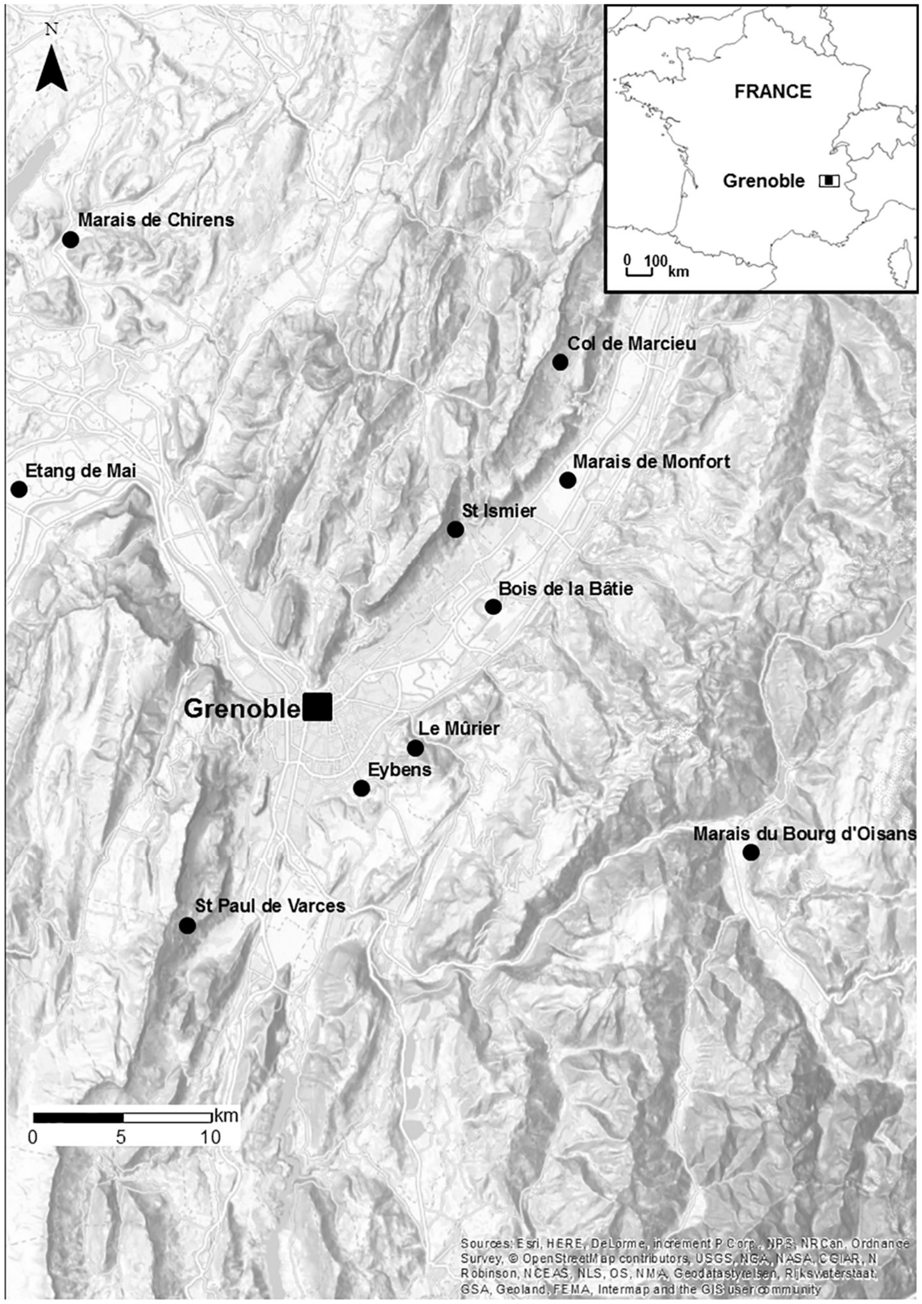

Fig. 1. Location of the field sampling plots in the Grenoble urban area.

network (*Espaces Naturels Sensibles*) (Fig. 1, Table C1 in Appendix C). Field work was conducted in summer 2016, besides AGB of 5 humid grasslands sampled in summer 2017.

2.3. Field methods

Based on the literature synthesis, field methods were developed separately for tree- and grass-dominated ecosystems. We defined specific protocols within each ecosystem type for the carbon pools of AGB, BGB, DOM. The same protocol was applied for the SOC of both ecosystems.

2.3.1. Forest

A 20-by-20m representative plot within each forest site was delimited, representing a compromise between areas usually applied for forest inventories in European and northern American temperate forests (Laflower et al., 2016; Lecomte and Rondeux, 2002; Timilsina et al., 2014). While this sampling design may not be ideal for capturing spatial heterogeneity, it reflects practice in forest studies.

2.3.1.1. Aboveground biomass. Field estimation of tree AGB was based on methods applied in national forest inventories in which allometric equations are used to link tree measurements from the field such as tree size, and sometimes wood density to tree biomass. Here, given large uncertainties associated with the measurement of height or wood density (Zianis, 2008) (see also Appendix D (Kattge et al., 2011)), we chose to consider only the diameter at breast height (DBH), i.e. the diameter measured at 1.3 m above the ground, of all trees with a dbh ≥ 5 cm. For multi-stemmed trees, all stems with a dbh ≥ 5 cm were measured. If possible, trees were identified to species level. All standing trees – dead and alive – were measured.

Based on Sileshi (2014); Zianis et al. (2005); Zianis and Mencuccini

(2004), we focused our choice on power law allometric equations, the typical form for allometric equations, i.e. $B = \alpha.D^{\beta}$, or, in its logarithmic form: $\ln(B) = \ln(\alpha) + \beta.\ln(D)$, where B is the total AGB and D the diameter at breast height. In some cases, we considered polynomial functions of dbh, but only of second degree functions as a third degree polynomial is biologically implausible (Sileshi, 2014).

We compared four different allometric methods – which of some have already been compared in the above cited studies – for estimating total AGB, including the stem, branches and leaves:

- a "universal" allometric equation, i.e. an equation that can be used for any tree species. We considered the universal theoretical model of West et al. (1999) to estimate the scaling exponents of allometric equations (see Zianis and Radoglou (2006)) for a presentation of this model). According to this model, b equals 8/3 (i.e. ≈2.67). For a we chose the value of 0.10 used by Zianis (2008) and Chambers et al. (2001). This model has been used in numerous studies comparing different allometric methods (Zianis, 2008; Zianis and Mencuccini, 2004; Zianis and Radoglou, 2006).
- a variant of this "universal" model by Zianis (2008), which uses the b value of Zianis and Mencuccini (2004), obtained by averaging b values from compiled studies (Table 1 of) with $b = 0.3679$. The a value was obtained from the same data set in Zianis et al. (2005), with $a = 0.1424$.
- allometric equations for different species groups defined by Jenkins et al. (2003). We considered this method as valuable for providing multi-species equations, although these equations were first established for American tree species. Each observed tree species was allocated to one of the 8 species groups (Table E1 and E2 in Appendix E).
- species-specific equations, mainly from Zianis et al. (2005) and the online platform GlobAllomeTree (www.globallometree.org) which shares and provides access to tree allometric equations (Table E3 in Appendix E). This fourth method was our reference method as it would be expected to be the most precise and accurate.

In the case of multi-stemmed trees, the two available approaches encountered during the literature review were applied to the four allometric methods. The approach of Doughty et al. (2016) considers a tree with several main stems as individual trees. The approach of Perring et al. (2015) deals with multi-stemmed trees by transforming measures into an equivalent unique stem, calculating the square root of the sum of the squared diameters of the individual stems.

The results of the four allometric methods were compared with the average values for different forest types by climatic zones as defined by the IPCC Tier 1 (IPCC, 2006).

To convert dry AGB to carbon storage, we used the carbon content value of 0.47 for temperate climate trees (IPCC, 2006), which is not significantly different from the stem carbon content of European tree and shrub species (Wilcoxon rank sum test W = 5, $P = 0.56$; Appendix D (Kattge et al., 2011)). For simplicity, we considered the same carbon content for stem and branches as well as for leaves as recommended for temperate and boreal zones (IPCC, 2006).

2.3.1.2. Belowground biomass. Given the prohibitive amount of field work involved, we chose to estimate BGB from AGB, as is often done using root-to-shoot ratios and relationships between above- and belowground biomass (Cairns et al., 1997; Mokany et al., 2006). Three generic methods were considered, as species-specific root-to-stem ratios are scarce:

- belowground-to-aboveground biomass ratios of Mokany et al. (2006), used by the IPCC (2006) and thus our reference method.
- the average root-to-stem ratios compiled by Cairns et al. (1997) by latitudinal zone. We did not consider root-to-stem ratios based on soil texture or tree type to keep a single method practicable for all plots.
- a regression equation predicting root biomass density from aboveground biomass density (Cairns et al., 1997).

To focus on the variation resulting from the choice of the BGB estimation approach, we used only one of the methods to estimate AGB. We focused on the "universal" model from Zianis (2008) as it is an easy method based on empirical data, combined with the Doughty et al. (2016) approach for multi-stemmed trees. BGB was converted into carbon stock with the same conversion factor as AGB (IPCC, 2006).

2.3.1.3. Dead organic matter

2.3.1.3.1. Litter. We considered a single method for estimating litter dry mass based on Chojnacky et al. (2009). Ten litter depth measurements were made at random locations within a plot. A regression equation between litter depth and litter dry biomass per unit area developed for the US Forest Inventory and Analysis was used to estimate litter mass from these depth measurements. Litter biomass was converted into carbon stock using a conversion factor of 0.44 (Chojnacky et al., 2009).

2.3.1.3.2. Dead wood debris. The diagonals of the 20-by-20 m plot were used as linear transects to estimate dead wood biomass. The diameter of all fallen dead wood debris with a diameter ≥ 5 cm was measured at their intersection with the transect. We compared the loss of accuracy across two threshold diameters: 5 cm and 7.5 cm. The 5 cm threshold diameter was our reference method as it included more dead wood debris. The dead wood debris volume was estimated with the following equation:

$$V = \frac{\pi^2}{8.\,L} \cdot \sum_1^n d_i^2$$

where V is the volume in m^3/ha; L is the transect length; n is the number of dead wood debris measured across the transect; and d_i the diameter at transect intersection of *the i*-th dead wood debris (p 260 in de Vries (1986)).

The volume was then converted to dry biomass with the expected wood density of fallen dead wood of a decay class 3 – the median of 5 classes across tree species: 0.26 g/cm^3 (Harmon et al., 2011). The conversion factor of 0.47 was used to convert dry biomass to a carbon stock (IPCC, 2006).

Table 1
Results of the statistical analyses performed on the forest AGB data (n = 10) comparing alternative methods (Jenkins, Zianis, West) to the reference method (Sp.) for two multi-stemmed tree approaches: Perring and Doughty.

	Perring			Doughty		
	Jenkins vs. Sp.	*Zianis vs. Sp.*	*West vs. Sp.*	*Jenkins vs. Sp.*	*Zianis vs. Sp.*	*West vs. Sp.*
Relative error	12.28	11.92	103.76	15.61	17.06	87.91
Linear regression	Estimate : 1.04 (0.07) $p < 0.001$, $F_{1,8} = 247.7$, R^2adj = 0.96	Estimate : 0.96 (0.12) $p < 0.001$, $F_{1,8} = 59.39$, R^2adj = 0.87	Estimate : 0.35 (0.06) $p < 0.001$, $F_{1,8} = 32.69$, R^2adj = 0.77	Estimate : 1.09 (0.11) $p < 0.001$, $F_{1,8} = 97.4$, $R^2_{adj} = 0.91$	Estimate : 0.94 (0.16) $p < 0.001$, $F_{1,8} = 36.07$, $R^2_{adj} = 0.80$	Estimate : 0.33 (0.08) $p < 0.01$, $F_{1,8} = 17.85$, $R^2_{adj} = 0.65$

2.3.2. Grasslands

In grasslands all measurements were taken along two linear 30-m transects.

2.3.2.1. Aboveground biomass. We quantified grassland AGB using a relationship between average sward height and dry biomass production, as established for mountain grasslands (Lavorel et al., 2011) and validated for mesophilic grasslands (Gos et al., 2016). For the 8 humid grasslands we calibrated regression models between the vegetative sward height and production (biomass per hectare) by sampling eight 50-by-50 cm quadrats located randomly along the two 30-m transects. Vegetative height was measured at four points within each quadrat, and vegetation of the entire quadrat was cut to ground level. Green biomass and litter were sorted in the laboratory, and weighed. Subsamples of at least 150 g were oven-dried at 70 °C for 48 h and then weighed, in order to estimate dry biomass weight for total biomass, green biomass and litter mass. Regression models were developed between the mean sward height (across the 4 sampling points) and both total and green biomass for each quadrat. Specific equations were developed for humid grasslands. The humid grassland data was then pooled with mountain grasslands (from Lavorel et al., 2011) to obtain general equations applicable to both types. Biomass values were log-transformed. All analyses were carried out with the software R (www.r-project.org).

The quality of the regressions was assessed with the adjusted R^2. The uncertainty of the regressions was quantified through the relative error calculated as the average variation of fitted values (*Fit*) compared to the measured values (*Meas)*:

$$\frac{100}{n} \times \sum_{j=1}^{n} \frac{|Meas_j - Fit_j|}{Meas_j}$$

where n is the number of data points.

The relative error is a scaled measure, expressed in percentage, of the absolute deviation from the fitted values compared to actual values and thus can be compared with other measures of deviation. It is considered as an individual calculation of the mean absolute percentage error, an accuracy measure (Hyndman and Koehler, 2006), but adapted for comparing methods by comparing pairs of values rather than comparing estimated values to a reference value (van Breugel et al., 2011).

We used three different estimations:

- The actual cut and weighed biomass of the sampled quadrats. As the most precise method, it was our reference method.
- Type-specific equations: an equation for wet grasslands and an equation for mountain grasslands.
- A generic equation combining the data from both grassland types.

Dry biomass was converted to carbon stock with the factor 0.47 (IPCC, 2006).

2.3.2.2. Belowground biomass. Considering the high variability of BGB-to-AGB ratios, in order to estimate the BGB in grasslands, we considered two common methods:

- generic values of belowground-to-aboveground biomass ratios of the Tier 1 of the IPCC (2006), using the measured total AGB: the ratio 4.0 was applied to humid grasslands and the ratio 2.8 to mesophilic grasslands. It was our reference method based on the IPCC report.
- a ratio of 1:1 between the AGB and the BGB (Dukes et al., 2005; Weigelt et al., 2005).

Dry BGB was converted to carbon stock with the 0.47 factor (IPCC, 2006).

2.3.3. Soil organic carbon

Soil carbon is usually calculated as the product between bulk density and carbon content (e.g. Wang et al. (2011)).

Bulk density was estimated for the first 5 first centimeters of soil depth using 8-cm diameter metal rings. Five samples were taken at regular distance along a 30-m linear transect within each forest or grassland plot. They were weighed and then oven-dried at 70 °C until weight stabilization. Then they were sieved at 2 mm and the dry soil was weighed.

For carbon content analysis, a composite sample was made with an auger at nine sampling points regularly located along two 30-m transects within each plot. At each point, one sample for each of three soil layers: 0–15 cm, 15–30 cm and 30–45 cm, was collected. The soil was air-dried and then sieved at 2 mm. A subsample was ground and oven-dried at 70 °C for at least 48 h. Around 10 mg were put in a tin capsule and analyzed by an elementary analyzer Flash EA which measured total carbon and nitrogen content (%). We discarded three plots from the analyses whose soil layer was < 45 cm – two dry forests on mountain slopes and one mesophilic grassland -.

We considered three alternative methods for a 45 cm depth:

- The estimation of carbon stored in the first 45 cm which was our reference for quantifying more exhaustively the soil carbon content
- The estimation of carbon stored in the first 30 cm multiplied by 1.5 in order to extrapolate the C stored in the 45 cm
- The estimation of carbon stored in the first 15 cm multiplied by 3 in order to extrapolate the C stored in the 45 cm.

2.4. Data analysis

We explored three dimensions of method comparisons. First we assessed the comparability of methods in terms of stock estimation; second we tested the consistency across methods and third we compared the associated uncertainties based on the relative error of each method. We also compared our estimates with external references. Data analysis was conducted separately for forests and grasslands. All analyses were carried out with the software R (www.r-project.org).

2.4.1. Comparability and consistency

To test the comparability of carbon stock estimates by different alternative methods for each carbon pool, we constructed linear models with the reference method as the response variable and an alternative method as the explanatory variable. Comparability was assessed using first the adjusted R^2 of the linear model which indicated the quality of the relationship – if any – between two methods, and second the estimate value of the linear model. Consistency was assessed using the adjusted R^2.

BGB of both forest and grassland ecosystems were estimated through constant ratios applied to the AGB, so the data were not independent. Thus these methods consistency was assessed through the comparisons of the overall estimations with t-tests for both the forest and grasslands BGB estimations (data normally distributed). The comparability of methods was not applicable as it was a comparison of ratios.

2.4.2. Uncertainty: relative error

We quantified accuracy of an alternative method compared to the reference method with the relative error (RE) between each alternative method and the reference method, so a derivation from the mean absolute percentage error (Hyndman and Koehler, 2006). As applied by van Breugel et al. (2011) for comparing an alternative method with a reference method across plots:

$$RE = \frac{100}{n} \times \sum_{j=1}^{n} \frac{|Var_{alt,j} - Var_{ref,j}|}{Var_{ref,j}}$$

where $Var_{alt,j}$ is the variable of the j-th plot estimated with an alternative method, $Var_{ref,j}$ the variable of the j-th plot estimated with the reference method and n is the total number of plots.

RE is a measure of the average variation of the alternative method compared to the reference.

2.4.3. Realism of carbon stock estimates

To test whether estimates of carbon stocks obtained with our methods are realistic we used t-tests to compare both reference and selected methods with reference value(s) from the (IPCC, 2006, 2003).

3. Results

3.1. Forests

3.1.1. Aboveground biomass

The Doughty and the Perring approaches for multi-stemmed trees were equivalent for all four allometric methods with linear model estimates close to 1 (between 0.97 and 1.07) and with $R^2_{adj} \geq 0.98$ (Table 1). The relative errors were 11% or less.

For the Doughty multi-stemmed tree approaches, the Jenkins and Zianis allometric methods did not differ from the reference method with slope estimates close to one (respectively 0.94 and 1.09), with closer slope estimates and smaller standard errors for the Perring approach. Also the adjusted R^2 had with values above 0.80 ($p < 0.001$) and mean relative errors around 15%. Thus these two methods were comparable and consistent with the reference method.

For both multi-stemmed tree approaches, the West allometric method overestimated by a factor 2 (RE of 104 and 88%) AGB compared to the reference method. Even if it is consistent with the reference method ($R^2_{adj} > 0.75$), the two methods were thus not comparable (slope estimates of 0.33 and 0.35) (Fig. 2B).

As the results for both multi-stemmed approaches were similar, the more straightforward Doughty approach was retained. Considering its easy application we retained the Zianis allometric method which does not require tree identification.

For the three remaining allometric methods – besides the West method – aboveground biomass estimates were within the IPCC value interval for temperate mountain forests (unilateral t-tests, $p < 0.05$), even if our estimates were different from the average values (Appendix F and Table G1 in Appendix G). Our estimations exceeded the upper value for temperate continental forests ($p > 0.05$).

3.1.2. Belowground biomass

The application of the average root-to-shoot ratio of Cairns et al. (1997) resulted in an estimation quite close to the IPCC ratio ($t = -0.33$, df = 15.90, $p = 0.74$), with a relative error of 8.33%. This was not the case for the regression equation predicting root biomass density from AGB density ($t = -3.40$, df = 11.05, $p < 0.01$) which overestimated BGB compared to the IPCC, and had a high dispersion with a relative error of 145%. We retained the IPCC (2006) method which is widespread and thus enables comparison with other studies.

For the three methods, BGB estimates were within the IPCC value interval for both temperate continental broadleaf and mountain forests with plots having an AGB either between 75 and 150 t/ha or an AGB higher than 150 t/ha (Appendix F and Table G1 in Appendix G).

3.1.3. Dead wood

The alternative threshold diameter of 7.5 cm was comparable and consistent with the reference method (5 cm) with a slope estimate of 1.01 (± 0.2) and a R^2_{adj} of 1 ($p < 0.001$, $F_{1,7} = 1931$) (Fig. 3B). However, dead wood volume estimations for the 7.5 cm diameter threshold were quite spread around the reference method estimates with a mean relative error of 31%. Thus, we retained a threshold diameter of 5 cm, consistent with the dbh measure threshold.

The results for both diameters were lower than the IPCC reference for deciduous forest (Appendix F and Table G1 in Appendix G).

3.1.4. Litter

Our litter carbon estimates (Appendix F) were located within the IPCC value interval for cold temperate moist forests and did not differ from the lower interval value for warm temperate moist forests (Table G1 in Appendix G).

3.2. Grasslands

3.2.1. Aboveground biomass

3.2.1.1. Green biomass. Equations for green dry biomass production for both grassland types had correlation coefficients of 0.64 and 0.65 for the mountain and the humid grasslands respectively, with an average variation around 20% of the fitted values compared to the actual values (Table 2). The relationship for both types considered together has a lower R^2 of 0.54 and an average variation of 25%.

3.2.1.2. Total biomass. Equations for total biomass had higher

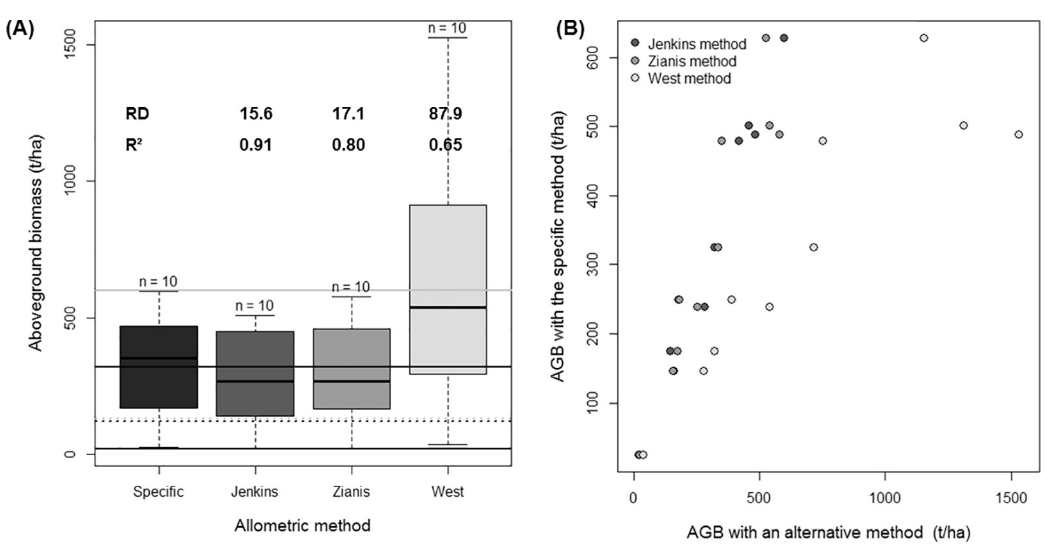

Fig. 2. (A) Forest AGB (in tons/ha) estimated by four different allometric methods. The top continuous black line is the upper value of the IPCC (2006) value interval of carbon stocks of temperate continental forests. The dotted black line is the IPCC average value of temperate continental forests. The continuous grey line is the upper value of the IPCC value interval of carbon stocks of temperate mountain systems. The dotted grey line is the IPCC average value of temperate mountain systems. The bottom continuous black line is the lower value of the IPCC value intervals of carbon stocks for both temperate continental forests and temperate mountain systems. (B) Linear regressions between both the AGB estimations by alternative methods and the reference method. n is the number of plots. RE is the average relative error compared to the reference method with the Doughty approach for multi-stemmed trees. R^2 is the adjusted correlation coefficient between the estimations of an alternative method and the reference method.

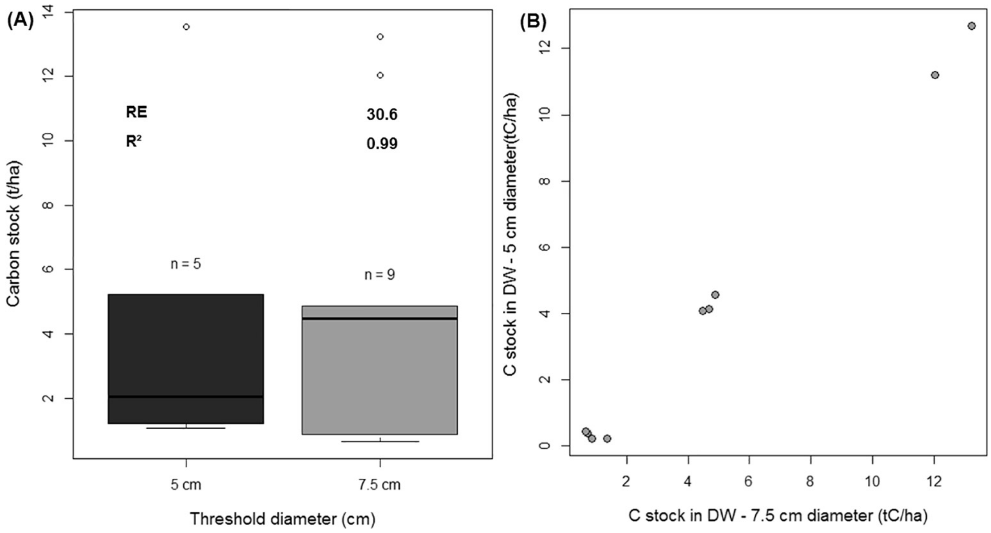

Fig. 3. (A) Dead wood carbon stock (in tons/ha) estimated with two different threshold diameters. (B) Linear regressions between the carbon stock estimations with both threshold diameters. *n* is the number of plots. RE is the average relative error compared to the reference method. R^2 is the adjusted correlation coefficient between the estimations of an alternative method and the reference method.

correlation coefficients than for green biomass with a value of 0.65 for the mountain grasslands, 0.71 for humid grasslands and 0.73 for both types together. The average variations were also lower: between 11 and 13% (Table 2).

Thus we retained the generic equation across grassland types for the total biomass given its higher correlation coefficient and the preference for a single model across grassland types. Moreover, considering total AGB is more relevant when aiming to estimate carbon stock.

Green biomass measures and estimations were higher than IPCC reference values for the peak aboveground live biomass (Appendix F and Table G1 in Appendix G).

3.2.2. Belowground biomass

The alternative method was not consistent with our reference method with a relative error of 70% (t-tests, $t = -6.27$, $p < 0.001$). We thus retained the application of the relevant IPCC ratio value for each grassland type.

All our biomass estimations were higher than the IPCC reference value for temperate grasslands (Appendix F and Table G1 in Appendix G).

3.3. Soil

The two alternative methods underestimated the carbon stocks with a slope of 1.31 when considering 3 times the C stock of the first 15 cm of soil and a slope of 1.25 when considering 1.5 times the first 30 cm of soil, with respectively a relative difference of 24 and 12% (Fig. 4). Both methods were consistent and comparable to the reference method with high R^2 of 0.85 and 0.95 ($p < 0.001$).

The retained method is the consideration of 30 cm because of its better R^2 and lower relative difference; it is also the usual standard depth (e.g. in InVEST). The slight underestimation from this method should however be kept in mind when used.

Our SOC estimations for the 30 first centimeters did not differ from all reference values besides the LAC (soil with low activity clay minerals) warm temperate moist value of the IPCC (Appendix F and Table G1 in Appendix G).

4. Discussion

We compared alternative methods for quantifying each of the carbon pools in forests and grasslands in terms of comparability, consistency and accuracy. As expected, more numerous methods were available for the forest AGB. Also, alternative methods for forest AGB and SOC provided estimates comparable to and coherent with a more detailed reference method, as attested by the high quality of linear relationships between their estimates. Moreover, the accuracy quantification supported protocol simplifications when an alternative method

Table 2
Linear equations with the vegetative height (in cm) as explanatory variables and the green or total dry biomass production (t/ha) as response variables. These equations are of the form ln(biomass production) = *a**height + *b*. SE is the estimate standard error and the associated *P*-value is the degree of significance of the intercept (*b*) and the slope estimate (*a*). R^2 is the adjusted correlation coefficient of the linear equations, *P* the *P*-value of the model and *F* the value of the *F*-statistics. *n* is the number of studied quadrats. The average RE (Relative Error) is the average variation of the fitted values compared to the actual values.

Grassland type	Regression coefficients (± SE)	*P*-value	R^2_{adj}, *P* *F*	*n*	Average RE (%)
Green biomass					
Mountain grasslands	$a = 0.0269$ (± 0.0018)	< 0.001	0.64, < 0.001	119	20.30
	$b = 0.5413$ (± 0.0511)	< 0.001	$F_{1,117} = 215.7$		
Humid grasslands	$a = 0.0174$ (± 0.0016)	< 0.001	0.65, < 0.001	64	19.51
	$b = 0.5242$ (± 0.0862)	< 0.001	$F_{1,62} = 211.3$		
Both types	$a = 0.0155$ (± 0.0011)	< 0.001	0.54, < 0.001	183	24.10
	$b = 0.7560$ (± 0.0420)	< 0.001	$F_{1,181} = 211.3$		
Total biomass					
Mountain grasslands	$a = 0.0254$ (± 0.0017)	< 0.001	0.65, < 0.001	119	13.20
	$b = 0.8057$ (± 0.0472)	< 0.001	$F_{1,117} = 224.7$		
Humid grasslands	$a = 0.0185$ (± 0.0015)	< 0.001	0.71, < 0.001	64	11.20
	$b = 0.9377$ (± 0.0807)	< 0.001	$F_{1,62} = 156.3$		
Both types	$a = 0.0193$ (± 0.0009)	< 0.001	0.73, < 0.001	183	13.31
	$b = 0.9375$ (± 0.0345)	< 0.001	$F_{1,181} = 484$		

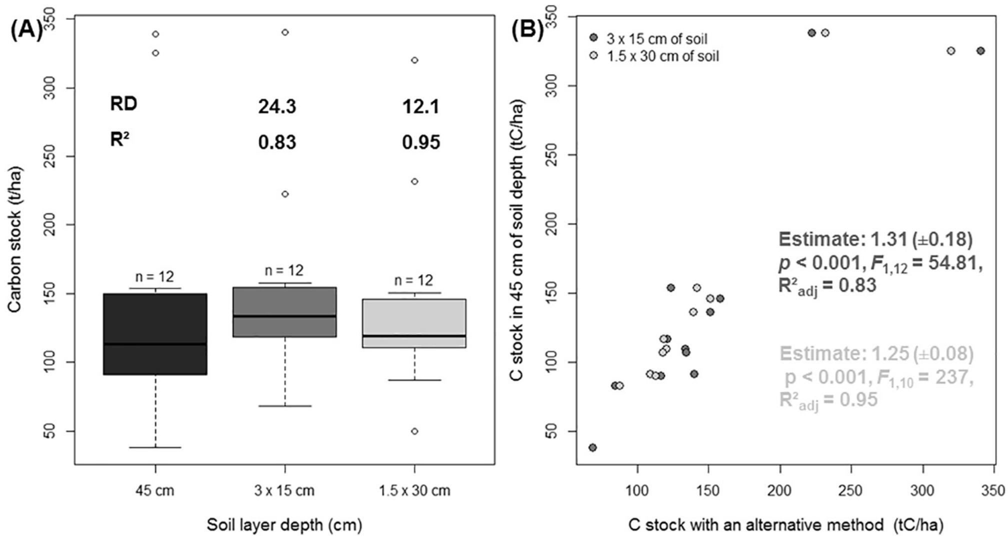

Fig. 4. (A) SOC stock (in tons/ha) estimated with three different methods: the stock of 45 cm soil depth, the stock of 30 cm of soil multiplied by 1.5 and the stock of 15 cm of soil multiplied by 3. (B) Linear regression between the carbon stock estimations of the two alternative methods and the reference method. *n* is the number of plots. RE is the average relative error compared to the reference method. R^2 is the adjusted correlation coefficient between the estimations of an alternative method and the reference method. The estimate is the slope value (± standard error) of the linear regression between the estimations of an alternative method and the reference method (dark grey for the 3 × 15 cm of soil and light grey for the 1.5 × 30 cm of soil), *P* the *P*-value of the model and *F* the value of the *F*-statistics of the model.

gave estimates which varied by less than 20% from the reference method and were comparable to reference values (IPCC, 2006). Only one method was available for the estimation of the litter carbon pool. Method simplification was not conceivable for grassland BGB because of too low accuracy. In the following we discuss the main sources of uncertainty for each carbon pool and consider their implications for possible method simplifications.

4.1. Forest carbon stocks

4.1.1. Biomass

The multi-species models from Jenkins et al. (2003) and the universal model of Zianis (2008) gave comparable and consistent estimates of AGB as compared to the species-specific method, and had equivalent accuracy. Consistent with previous analyses (Zianis and Mencuccini, 2004; Zianis and Radoglou, 2006), the universal theoretical model of West et al. (1999) was rejected due to consistent overestimates. For two complementary data sets in the same region the multi-species method tended to be more accurate (Appendix H). Specifically, the universal model produced a high mean error (~30%) for mountain forest plots, which may reflect the lack of equations calibrated in mountain areas in the model compilation (Zianis and Mencuccini, 2004). Nevertheless the benefits of the universal method, minimizing field time, and year-round practicability for non-expert practitioners should be considered for mountain forests for which species-level equations did not improve significantly the diameter – biomass relationship from the functional group level.

Consistent with discrepancies with IPCC values already reported for temperate moist forest (Keith et al., 2009), possibly due to diversity of forest ecosystems included in the “temperate” biome, our aboveground carbon stock estimates were significantly higher than IPCC average values. We suspect this to reflect the influence of mountain plots, which consistent with complementary analyses for plots across the Alps (Appendix H), have higher IPCC reference values. Also the inclusion of forest plots from higher altitudes could drive this overestimation. Indeed, wood specific density has been reported to increase with altitude (Culmsee et al., 2010; Girardin et al., 2014), but this is not reflected in the allometric equations we used, which only depend on diameter at breast height.

Lastly, the increasing availability of remote sensing technology, for ES quantification (de Araujo Barbosa et al., 2015) offers alternative approaches for quantifying forest aboveground carbon stocks. For example, Zhang and Kondragunta (2006) combined MODIS images with allometric models based on foliage characteristics to estimate tree biomass. Radar data can identify individual trees and estimate their height and crown size to which then allometric relationships can be applied (Jucker et al., 2017).

BGB estimation in forests usually applies root-to-shoot ratios or other functions linking BGB to AGB. The often used IPCC standard value enables comparability across studies. The BGB carbon pool is however prone to high uncertainty as it cumulates uncertainties stemming from AGB estimation methods with those of a unique root-shoot ratio. For example, the IPCC ratio for temperate broadleaf forest with an AGB < 75 t/ha is 0.46 with a range from 0.12 to 0.93, and such ranges of as much as 5-fold are reported for forests with 75 < AGB < 150 t/ha (0.13–0.37; average: 0.23) or AGB > 150 t/ha (0.17–0.44; average: 0.24) (IPCC, 2006).

4.1.2. Dead organic matter

Our underestimation for dead wood carbon stock compared to the IPCC values for deciduous forests could be due to the inclusion of standing dead trees and stumps additionally to the fallen dead wood debris (Harmon et al., 2001). But our estimates for carbon stocks of litter biomass were congruent with the low value of the IPCC confidence intervals for warm and cold temperate moist climate zones (IPCC, 2006).

Linking litter depth to its biomass avoided time-consuming field sampling as done for the US Forest Inventory and Analysis program (Domke et al., 2016). This fast approach allowed us however to include within-plot variability as the litter carbon pool varies according to tree species (Woodall et al., 2012) and thus varies at fine scale (Smit, 1999). Thus local litter depth measurements might be more relevant than default values from the IPCC or country-specific models (Domke et al., 2016).

Estimates of fallen dead wood are highly sensitive to threshold diameter (Rondeux and Sanchez, 2010). The selection of 5 cm provided greater accuracy, as with a 7.5 cm threshold diameter one third of the dead wood carbon stock was ignored. Similar to the Swiss national forest inventory and to the Canadian protocol (Cros and Lopez, 2009), we applied transect sampling which is less time consuming and provides greater precision with respect to sampling effort than working in a fixed area (Ligot et al., 2012; Woldendorp et al., 2004). However, the transect method might not be relevant for dispersed dead wood debris (Woldendorp et al., 2004). Lastly, other methods may consider additional stocks such as standing dead trees (Anderson-Teixeira and DeLUCIA, 2011) or stumps (Cros and Lopez, 2009).

4.2. Grasslands

A simple measure of vegetative height provided an easy estimation

of grassland aboveground carbon stock using the generic equation for total biomass across mountain and humid grasslands. Our overestimations of the green biomass compared to the IPCC reference value might be due to a selection of more productive grasslands compared to average grasslands considered in the IPCC, though the range of considered grasslands and associated productivity for the IPCC was not available. Moreover, a high error of 75% was reported for this standard value (IPCC, 2006). Still, our biomass estimations were comparable to published measures of average production of French grasslands (Smit et al., 2008), and French permanent grasslands (Michaud et al., 2015).

The relevance of estimating the AGB grassland carbon stock is debatable since for numerous herbaceous species, this stock exists only for one growing season in alpine grasslands as in humid grasslands. The main utility for its measurement is deriving belowground carbon stocks. Grasslands have very significant belowground carbon pools (Hui and Jackson, 2006), as confirmed by BGB-to-AGB ratios greater than one. Using a reference ratio greatly simplifies estimates by bypassing field sampling, but propagates uncertainties associated with the AGB estimation. Also the IPCC and other ratios have high errors: 150% for the ratio of prairie grasslands and 95% for semi-arid grasslands (IPCC, 2006). Our overestimation of this carbon stock using the IPCC ratio compared to the IPCC reference value is due, as mentioned above, to the overestimations of green biomass compared to the IPCC peak aboveground live biomass. Moreover, the variation of BGB-to-AGB ratios as much as between 2 and 25 is another source of variation, as observed across grassland types in an alpine valley (Tappeiner et al., 2008), with a median ratio of 4, so a value comparable to the IPCC reference. The use of IPCC reference values allows comparability with other studies. However, if local BGB-to-AGB ratios are available, we recommend their use instead of IPCC values.

Lastly, new technological tools, such as field spectrometry, based on the measurement of various vegetation indices, may provide alternative methods for estimating AGB in grasslands. AGB is highly correlated to water absorption measures (Numata et al., 2008) and to the normalized difference vegetation index (NDVI) (Raynolds et al., 2012) while plant height is correlated to the enhanced vegetation index (EVI) (Cunha et al., 2010). These parameters can be reliably measured with a field spectrometer (Cunha et al., 2010; Mašková et al., 2008), thus substituting equipment for manpower.

4.3. Soil organic carbon

For the SOC stock, which has an essential role in mitigating global climate change (Lal, 2004), we validated the validity of sampling at 30 cm soil depth (IPCC, 2006) as used by models such as InVEST (Nelson et al., 2009), for extrapolating stocks to 45 cm, when relevant. However, in grassland ecosystems most of the carbon can be stored deeper than 30 cm (Ward et al., 2016). Deep SOC is also important in forests (Jobbágy and Jackson, 2000), as we observed for alluvial forest sites. Uncertainty across tested methods was low (12%), however, efforts should be invested into grassland SOC pools given their significance. Further methodological refinements may thus consider deeper layers and/or measure bulk density of different layers (Ward et al., 2016). With the improvements of new technologies, it will be soon possible to estimate SOC stocks using visible and near (or mid-) infrared reflectance spectrometry in the laboratory (Winowiecki et al., 2016) or even directly in the field (Cambou et al., 2016).

4.4. Estimating carbon pools for environmental assessment

The proposed set of easy methods for quick estimation of carbon stocks at plot scale was developed in response to the necessity of integrating ES assessment into land management and land planning (Albert et al., 2016). Given that the accuracy level of selected indicators was 10–20% compared to the reference methods assumed to be the closest to actual carbon stocks, their application is appropriate for estimating impacts of land use change or new ecosystem management if greater than 20%. Such impacts include, for example, severe thinning management practices in the USA which reduced AGB by 40% in US forests 6 years after treatment (Burton et al., 2013) and selective logging in Malaysian forests which reduced forest AGB by more than 50% (Pinard and Cropper, 2000). Fertilisation is the most common practice to increase grassland AGB (e.g. +32% in Lee et al., 2010), but it can have undetectable impact in BGB (+6% in Lee et al., 2010). Other practices like sowing of native and non-native grassland species had substantial effects on both AGB (increase of more than 200% of the biomass at the vegetation peak) and BGB (increase between 60 and 250% of root biomass. In the same experiment, perturbations like litter removal and soil raking would not be detectable with our simplified methods (−3% AGB and +13% BGB) (Foster et al., 2007).

Fertilization has been shown to have highly variable effects on SOC (Conant et al., 2001; Paustian et al., 1992) in the medium term due to floristic changes and possible increases in SOC mineralisation resulting from increased grazing intensities (Klumpp et al., 2009). Changes in grassland management can lead to detectable SOC increases by 15% in case of fertilizer use reduction in short duration leys or decreases by 26% in case of fertilization of a permanent grassland (Soussana et al., 2004). Other management changes leading to smaller changes such as intensified use of permanent grasslands (+7%) or the conversion of permanent grassland to medium duration leys (−4%) (Soussana et al., 2004) would be unlikely to be detected with a simplified method.

Our methods also apply to comparisons of ecosystems before/after restoration when degradation released of at least 20% of initial carbon stocks. For, example, less than 15 years after restoration or creation of wetlands, SOC was still only 33–74% of a reference wetland value (Moreno-Mateos et al., 2015). In riparian forest restoration, our simplified methods would have detected deficits of 50% for AGB and 30% for SOC between an old restoration site and intact remnant forest (Matzek et al., 2016). In Australian degraded semiarid ecosystems our simplified method would barely detect the 17% deficit in SOC after top soil restoration compared to a natural soil, but would definitely detect the 82% deficit when waste soil was used instead (Muñoz-Rojas et al., 2016).

4.5. Decision tree for method selection

Based on our quantitative comparison of methods, our uncertainty assessment and the different points discussed above, we propose a decision tree to guide practitioners and scientists in their method selection for each of carbon pool of both woody and herbaceous ecosystems (Fig. 5). This decision tree represents best possible compromises between precision, manpower and financial resources. We encourage practitioners to test it and assess benefits of recommended rapid methods.

5. Conclusions

We compared for the first time different methods of carbon stock estimation of varying complexity for each of the four main carbon pools. With this, we aimed to provide guidelines to scientists and practitioners aiming to estimate the ES of global climate regulation by estimating ecosystem carbon stocks. We identified fast, replicable and simple methods for each pool, thereby addressing our operational objective. In spite of their relative simplicity, the recommended methods were comparable with our more detailed reference methods, and are compromises between the necessary sampling effort and the associated precision in carbon stock estimation. These methods could be soon supplemented by new technologies linked to remote sensing and reflectance spectrometry. Given the uncertainties associated with different pools, we strongly recommend considering them separately, as each pool has its own source of estimation variability; for example, the compound uncertainty from the belowground biomass pool.

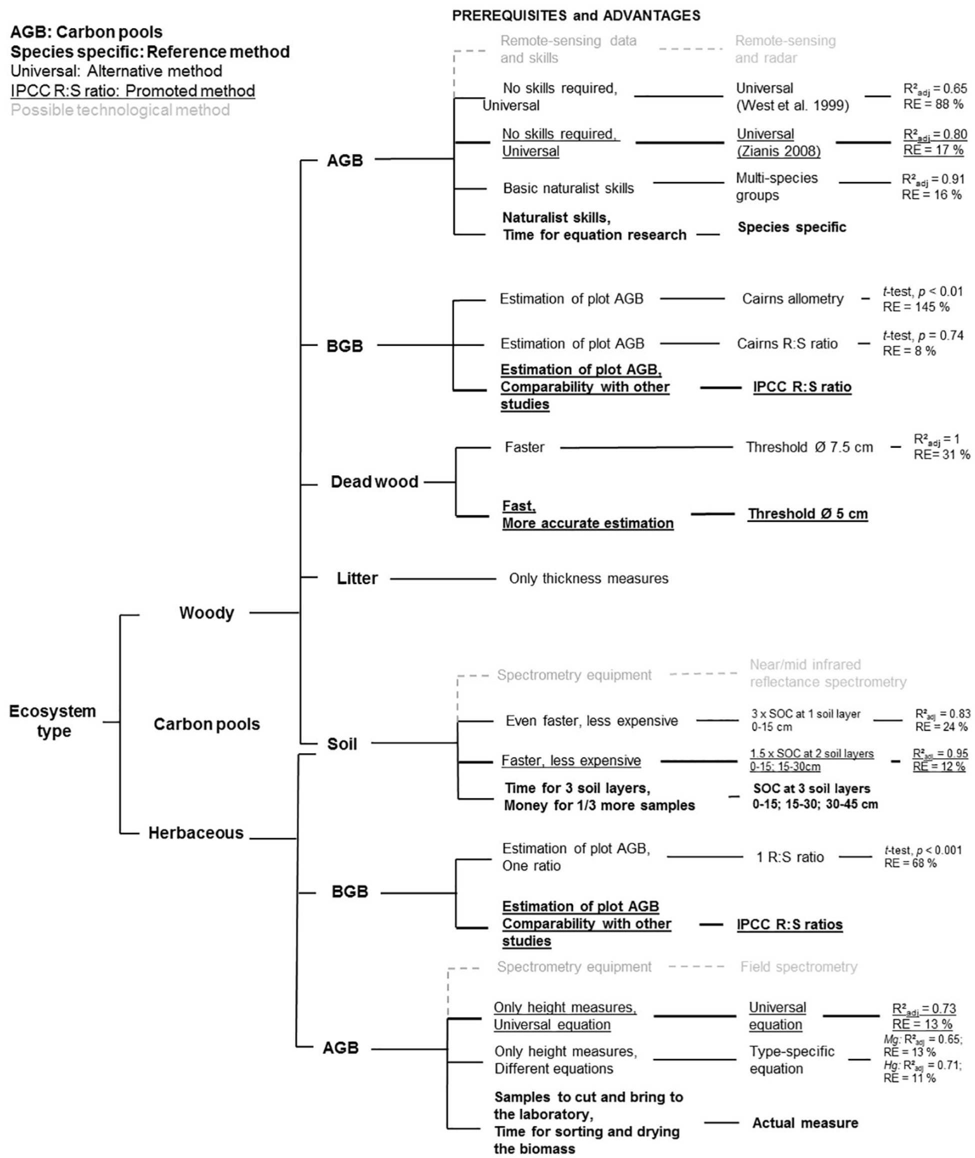

Fig. 5. Different methods for each considered carbon pool with the associated uncertainty compared to the reference method: the relative error (RE), the correlation coefficient (R^2) and, when relevant, the results of the *t*-tests. The method prerequisites and/or advantages are also presented. AGB stands for aboveground biomass, BGB stands for belowground biomass, Ø for diameter, *Mg* for mountain grasslands and *Hg* for humid grasslands. The bold branches are the reference methods, the branches with underlined text are the promoted methods and the black non-bold branches are alternative non-promoted methods. The grey branches are possible future technological methods.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.ecolind.2018.07.054.

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